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The Weakness of the Gini Coefficient in Farm States

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Executive Summary

Over the past couple decades, the gap between the highest and lowest incomes has increased rapidly in the United States. The Great Recession and the events since have caused voters, politicians, and researchers to become more aware of the importance of this disparity. General interest has sparked academic studies of the issue in many fields of expertise such as psychology and economics. These researchers, in general, conclude that income inequality emanates from education gaps and other demographic and economic characteristics, but researchers have given a lot less attention to the tools used to measure it.

The present study focuses on the primary measure used to gauge income inequality, the Gini index, questioning its validity in states with a high share of income coming from agriculture. Investigating the five states with the largest ratios of farm to nonfarm income for the years 2010–14, the study concludes that the existence of a high proportion of farm income statistically alters the estimated Gini coefficient for all five states. Results thus undermine the usefulness of the Gini index in measuring income inequality for states with large farm sectors. A new tool should be created to account for these factors, or these factors should be considered and calculated differently when using the Gini index.

Introduction

Over the past several years and in recent election debates, income inequality has become a widely debated topic of public interest. Furthermore, it has been widely accepted that US income inequality has increased dramatically over the past several decades. Researchers typically use the Gini index to measure income inequality among states and nations. The index, developed in 1912, measures the distribution of income with a score ranging between zero (where a single individual has all the income) and one (where income is evenly divided among all).

As expected, the Gini coefficient relies heavily on the definition of income. However, measurements of income differ depending on such factors as tax credits, exclusion of capital assets, and subsidies. Since the definition of income varies significantly, the value of the Gini coefficient depends heavily on the definition. For example, in terms of filing federal tax returns, many exceptions and exemptions are made according to the individual taxpayer's situation, which renders income comparisons less meaningful. Differences in measuring income among countries or states can lead to massively skewed data with potentially questionable measures of income inequality.

Income derived from certain industries can further reduce comparability. For example, farm income is not comparable to nonfarm income for a variety of reasons. In 2014, federal support payments represented 8.7 percent of total farm earnings. Moreover, government payments are not evenly distributed: they go only to farms producing certain agricultural commodities, and the largest farms receive a disproportionate share of the payments. The effect on income distribution, then, is to increase the incomes of the top quintile of farm households by up to twice the amount of the third quintile of households (Mishra et al. 2012).[1]

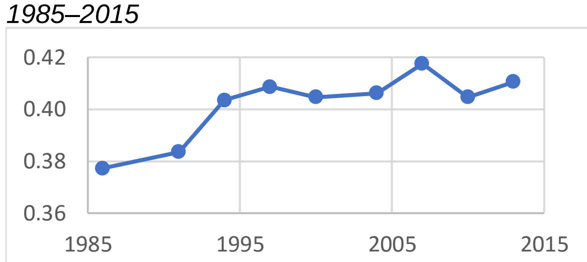
Farm income also does not compare well with nonfarm income because farmers make greater use of tax credits than nonfarm households and nonfarm enterprises. Farmers also often invest in large capital assets that amortize or depreciate over time. To the extent that the depreciation charges do not match the actual decline in value, farm income is mismeasured. The USDA determined that on average, farms reported before-tax household income reduced by more than 25 percent to compensate for business losses. In contrast, only 4 percent of nonfarm businesses incurred losses that reduced reported before-tax household income (Mishra et al. 2012, 34). These two differences alone bring up questions of validity in these states among others.

The present study will focus on the five states with the highest 2014 farm income as a percentage of total income. The states with the highest share of income[2] produced by the farm sector in descending order for 2014 were South Dakota, Nebraska, Iowa, North Dakota, and Idaho.[3]

Literature Review

As shown in figure 1, over the last three decades, income inequality in the United States has increased substantially, as

***Figure 1**: Gini coefficient of the United States, 1985–2015*



Source: World Bank

[1] http://www.ers.usda.gov/media/889402/aer812g.pdf. Accessed May 25, 2016.

[2] Throughout this study, farm income includes income from crop and animal production.

[3] Except for Idaho, each of these five states is located in the West North Central region in the US Census. Thus other important factors influencing the Gini coefficient are, to a degree, reduced.

indicated by the Gini coefficient, which rose from 0.38 in 1986 to 0.41 in 2013. In the past five years, however, income inequality has not increased as drastically.

Researchers tend to conclude that income inequality is exacerbated by gaps in education (Muller 2002), by an aging labor force (Drosdowski, Stover, and Wolter, 2015), and by the presence of concentrated populations (Glaesar, 2009). Scholars such as Gastwirth (1972, 2016) admit that the Gini coefficient is artificially skewed: "The method used by the Census Bureau often leads to estimates which are outside of mathematically possible bounds." However, few researchers call into question the industry source of income.

Little research has been done on the effect of farm income on the Gini coefficient, but a previous study examined the role of government payments to households with farm income. The study, conducted for the different farming regions of the United States and the years 1996–2001, concluded that government support payments did account for variations in the Gini coefficient and that with higher government payments, the Gini coefficient is lower than it would be otherwise (Mishra, El-Osta, and Gillespie 2009), although those government payments do not include disaster-relief funds.

Income inequality has also been found to be greater in farm households compared to nonfarm households. In 2001, the bottom 60 percent of farm households only had 23.3 percent of total farm income, and government payments correlate moderately with total income (Mishra et al. 2002). It should be noted these studies were conducted when the FAIR Act was in place.

The most recent bill affecting farm income is the Food, Conservation, and Energy Act of 2008. Limits of payments were set to $40,000, $65,000, and $75,000 per entity depending on the program type, among other limitations to specific types of farming such as cotton farming and dairy farming, which is argued to hurt the farm industry (Harris et al. 2008). This may be why the results in this study are different than the results in the previous studies. There used to not be such tight caps on government support payments, which often made the Gini coefficient lower than it otherwise would be. With all of those caps put in place by that farm bill, the income of households with farm income has decreased, meaning the Gini coefficient has risen in states with large agriculture sectors.

The impact of crop versus livestock farming along with greater use of tax deductions by farmers has not been taken into account in measures of the Gini coefficient, although they both do impact farm income. Certain types of farming receive more government support payments than others, and crop farmers are more like to be affected by droughts, meaning more farm losses.

Other studies have focused on the calculation of the index. The Gini coefficient is the result of the estimated difference between the slopes along the Lorenz curve. This can cause mathematical errors from the inclusion of negative incomes. Economists have tried to correct for these errors by using revised statistical models that limit different aspects of the formula. Perhaps the Gini coefficient is not the best tool to use for calculating income inequality.

Data and Methodology

The Gini coefficients for all 355 of the counties of the five states were collected from the US Census Bureau for the years 2010–14, while data on 2010–14 farm and nonfarm income comes from the Bureau of Economic Analysis. Farm income here is the total reported income from farmers in each county. Indicators for each state (either 0 or 1) were used. The indicator for Idaho was omitted as the comparison state. Factors that past research has concluded as influencing income inequality were also calculated by county. These include education—measured by the percentage of the population with a high school degree or higher—race, age, percentage of births to unmarried mothers, and population density.

The dependent variable, the Gini coefficient, is a measurement ranging from 0 to 1, with 0 meaning the most equal income distribution (perfect equality) while 1 means one individual has all the income (perfect inequality).

A fixed-effects model was used instead of an OLS regression to account for the variation of error terms and variation in the Gini coefficient over the years that were not otherwise captured by the independent variables.

This research produced initially puzzling results when analyzing farm income. Results vary across states. While an increase in farm income in Idaho decreases the Gini coefficient, a similar increase in North Dakota and South Dakota demonstrates that as farm income as a share of total income increases within their counties, so does their Gini coefficient. There are a couple reasons for these differences, such as government support payments and the relative amount of crop farming versus livestock farming in each state. Figure 2 shows the differences in the amounts of government payments by state. Idaho has the lowest amount of government payments, whereas all the other states have relatively larger amounts of government payments, which is why Idaho's results differ from the other states. Also note that for all years except 2014, North Dakota and South Dakota received the least amount of government support payments, which may be why their Gini coefficients rise the most as farm income increases. Figure 3 shows the amount of livestock cash receipts versus crop cash receipts by state and year. Note how Idaho has less overall cash receipts, but also relatively more livestock receipts compared to crop receipts, which can account for Idaho's differences in government support payments and outcomes in this regression. Also, South Dakota and North Dakota have relatively more crop receipts than livestock receipts, further explaining their change in the Gini coefficient resulting from differences in farm income.

Table 1 gives further insight as to the characteristics of the counties based on their Gini coefficients, while table 2 shows which states have the most equal and most unequal counties. The highest amounts of farm income as a percentage of total income are in both the highest and lowest quintiles, which once again is explained by the relative amount of government payments along with crop versus livestock farming. The states in the fifth quintile had the highest percentage of births to unmarried mothers, the lowest population density, and the lowest percentage of white population, as one would expect. North Dakota and South Dakota both have the largest number of counties in quintile five (the most unequal counties) and also have the most distortion to their Gini coefficient, as shown in table 4.

Policy Implications

As stated previously and by other researchers, the Gini coefficient is not a reliable tool to measure income inequality and therefore should not be used to set policies aimed toward reducing the inequality. Limits on government support payments due to the most recent farm bill and the Great Recession of 2008 mean past research results differ from what results today show. Farm households' income is going to vary greatly due to government payments, larger use of tax deductions, and crop versus livestock receipts, among other factors. When it comes to making policy decisions, the Gini coefficient should be altered in order to account for the variation in income across industries or not be used at all. The tool dates back to 1912. It has been over 100 years since this tool was created, so perhaps it is time the Gini index should be forgotten and a new tool used to measure income inequality. Farm income also should not be taken into account when calculating the Gini coefficient for policies that do not affect farm income. And when making policies for households with farm income, the index should be calculated only using that income. It is not wise to use a tool to make policy decision that is distorted by a certain industry of income where that industry makes up a high proportion of the state or county's total income.

Conclusion

After examining the Gini index in five farm states in the United States, I find many weaknesses in the measurement. This study has demonstrated farm income statistically alters the Gini coefficient for Nebraska, Idaho, Iowa, South Dakota, and North Dakota. Therefore, the Gini coefficient is not a proper tool to accurately measure income inequality in regions that differ significantly in the relative size of the farm sector. As income inequality has become a growing issue of importance, policy makers should take into account the flaws with the Gini coefficient before making decisions and evaluate the inequality differently so poor decisions are not made.

Appendix 1: County Data

Table 1: Description of county data, grouped by Gini coefficient, 2014

Quintiles	**Gini average**	**Farm income as % of total income**	**% white**	**% of births to unmarried mothers**	**Median age**	**% with a high school degree**	**Population density**
One	0.388	0.16816	94.9%	23.2%	41.5	33.1%	43.7
Two	0.414	0.15692	92.7%	29.3%	42.1	32.3%	24.6
Three	0.428	0.12185	93.7%	27.6%	42.1	30.6%	41.9
Four	0.445	0.16282	92.4%	26.5%	42.8	30.0%	39.3
Five	0.482	0.17330	84.7%	31.4%	41.8	31.8%	20.9

Table 2: Profile of counties by Gini score, 2014

	% of counties, grouped by Gini quintile				
Quintile	North Dakota	South Dakota	Nebraska	Iowa	Idaho
One	5.7%	13.6%	23.7%	23.2%	31.8%
Two	11.3%	18.2%	23.7%	23.2%	15.9%
Three	15.1%	15.2%	20.4%	26.3%	20.5%
Four	20.8%	21.2%	20.4%	19.2%	18.2%
Five	47.2%	31.8%	11.8%	8.1%	13.6%
Total	100.0%	100.0%	100.0%	100.0%	100.0%

Appendix 2: Regression Model and Results

Table 3: Variable definitions for regression variables	
Variable name	**Definition of variable**
Gini coefficient	2010–14 Gini coefficients for each county in the five-state area.
FarmIncRatio	2010–14 farm income as a percentage of the total income for all counties In all five states.
Age	Median age of the population for all counties
HighSchool	Percentage of the population with a high school or higher educational degree
PopDensity	County population per square mile
NE	A binary variable equal to 1.0 for all Nebraska counties, and equal to 0 for all non-Nebraska counties
SD	A binary variable equal to 1.0 for all South Dakota counties, and equal to 0 for all non–South Dakota counties
IA	A binary variable equal to 1.0 for all Iowa counties, and equal to 0 for all non-Iowa counties
ND	A binary variable equal to 1.0 for all North Dakota counties, and equal to 0 for all non–North Dakota counties
INE	Nebraska's farm income as a percentage of total income times the indicator variable, Nebraska
ISD	South Dakota's farm income as a percentage of total income times the indicator variable, South Dakota
IIA	Iowa's farm income as a percentage of total income times the indicator variable, Iowa
IND	North Dakota's farm income as a percentage of total income times the indicator variable, North Dakota
Percent_White	Percentage of white population out of total population.
Percent_Birth	Percentage of births to unmarried mothers out of the total births for each year.

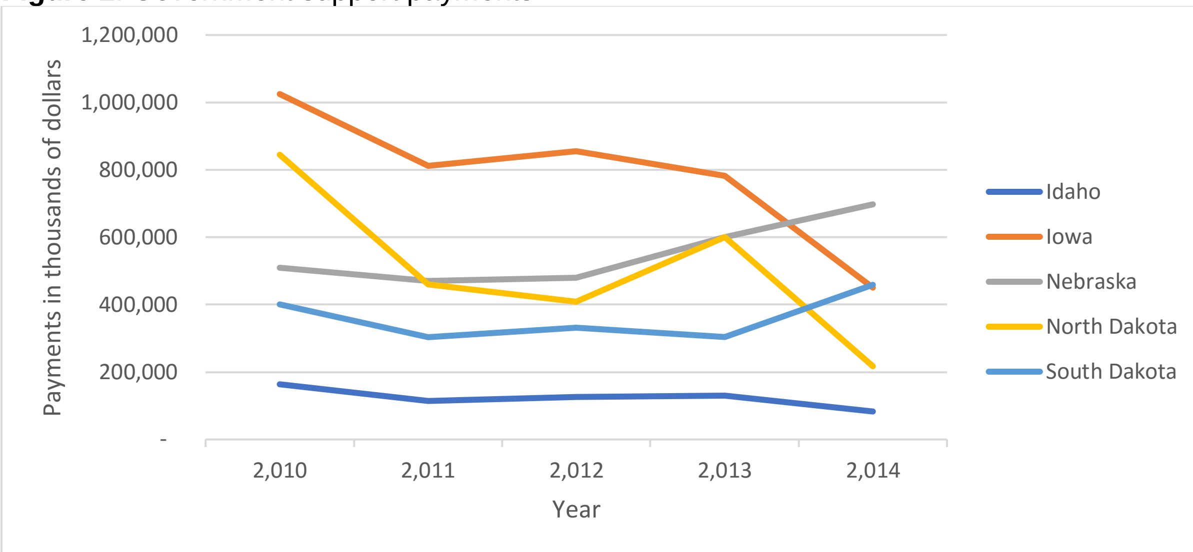
Regression model:

Gini coefficient = β_0 + β_1 FarmIncRatio + β_2 Age + β_3 HighSchool + β_4 PopDensity + β_5 NE + β_6 SD + β_7 IA + β_8 ND + β_9 INE + β_{10} ISD + β_{11} IIA + β_{12} IND + β_9 Percent_White +β_{10} Percent_Birth + μ Year

Results:

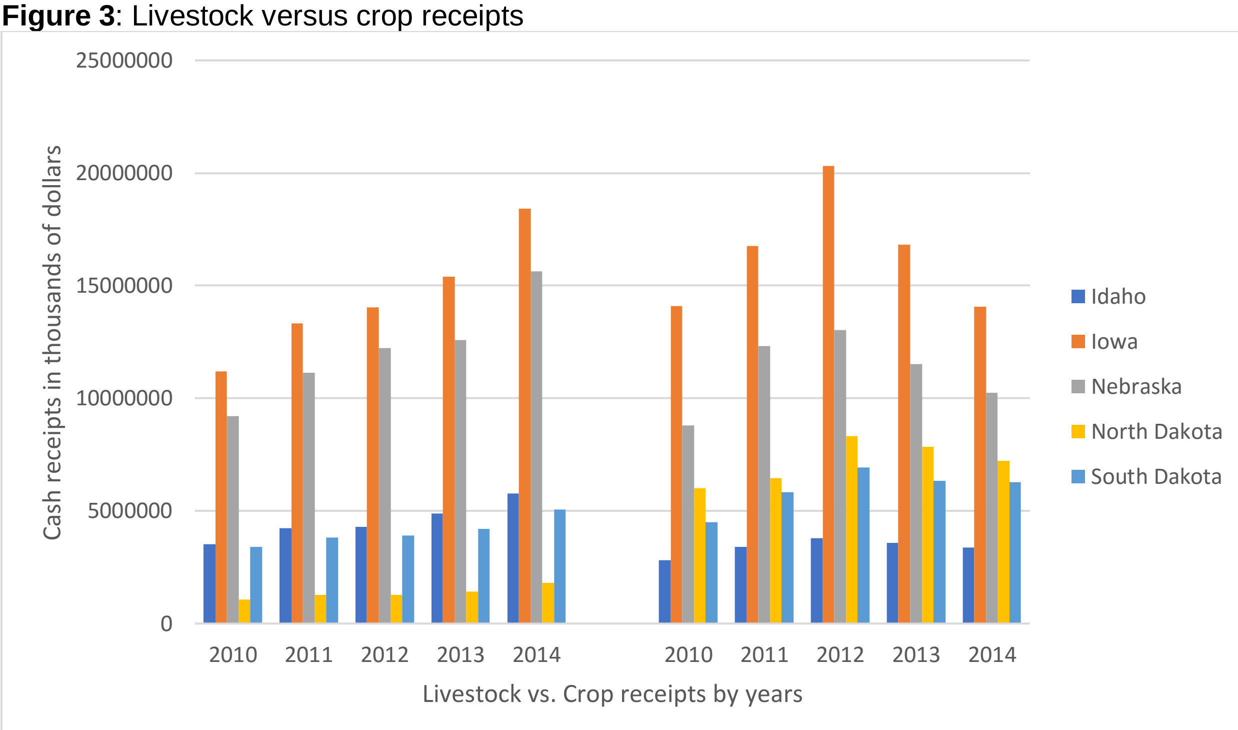
Table 4: Factors influencing 2013 county Gini coefficients	
	Coefficient (Standard error)
Intercept	0.463 [a] (0.009)
Farm income as % of personal Income (IA)	0.065 [a] (0.029)
Farm income as % of personal income (ID)	-0.086[a] (0.023)
Farm income as % of personal income (ND)	0.102[a] (0.028)
Farm receipts as % of personal income (NE)	0.014[a] (0.004)
Farm receipts as % of personal income (SD)	0.116[a] (0.006)
Age	0.0006 [a] (0.001)
% HS	-0.0001 (0.0002)
Population density	0.00002 [a] (9.30e-06)
Nebraska	-0.012 [a] (0.004)
South Dakota	0.013[a] (0.004)
Iowa	-0.002 (0.009)
North Dakota	0.020 [a] (0.004)
% births to unmarried mothers	-0.001 (0.004)
% white	-0.079 [a] (0.008)
2011	0.002 (0.002)
2012	0.006 (0.002)
2013	0.012 (0.002)[a]
2014	0.014 (0.002 [a]
Number of observations	1775
R-squared	0.255
F value	28.28
Robust standard errors in parentheses [a]Indicates that coefficient is statistically significant at 95% level of confidence	

Figure 2: Government support payments



Source: BEA

Figure 3: Livestock versus crop receipts



Source: BEA

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